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| Keywords (separated by "-") | Concept mapping - Evaluation - Knowledge integration maps - Science education - Network analysis | |

# Chapter 2
# Making Sense of Knowledge Integration Maps

**Beat A. Schwendimann**



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**Keywords** Concept mapping • Evaluation • Knowledge integration maps • Science education • Network analysis

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# 1 Introduction [AU1]

Concept maps are rich sources of information about students' understanding and can be used as complementary assessment items in the pretest and posttest (Rice, Ryan, & Samson, 1998). Concept maps can serve as sources for several different forms of information: presence or absence of connections, quality of connections, different types of link labels, different types of networks, and spatial placement of concepts. Many existing analysis methods do not capture the manifold alternative concepts students represent in a concept map and tend to lose information by representing concept map scores as a single number, for example by scoring components of the concept map qualitatively by counting the number of concepts, links, hierarchy levels, and examples (Novak & Gowin, 1984); by qualitatively evaluating propositions (McClure, Sonak, & Suen, 1999); or by comparing the students' concept map with a benchmark map (for an overview of concept mapping analysis methods see Cathcart, Stieff, Marbach-Ad, Smith, & Frauwirth, 2010). However, no single scoring method can accurately describe all different forms of information in concept maps. This chapter introduces a novel form of concept map, called knowledge integration map (KIM), to illustrate the need for a more comprehensive multi-level analysis method for concept maps. KIM analysis combines propositional, network, and topological analysis methods. Using quantitative and qualitative analysis methods in combination can provide complementary insights of connections between concepts and allows tracking changes in the quality of concept maps.

## 1.1 *Concept Maps and Knowledge Integration*

Concept map activities can support eliciting existing concepts and connections through the process of visualizing them as node-link diagrams. The explicitness and compactness of concept maps can help keeping a big picture overview (Kommers & Lanzing, 1997). The "gestalt effect" of concept maps allows viewing many concepts at once, increasing the probability of identifying gaps and making new connections. Generating concept maps requires learners to represent concepts in a new form which can pose desirable difficulties (Bjork & Linn, 2006; Linn, Chang, Chiu, Zhang, & McElhaney, 2010)—a condition that introduces difficulties for the learner which slow down the rate of the learning and can enhance long-term learning outcomes, retention, and transfer. The process of translating concepts from texts and images to a node-link format may foster deeper reflection about concepts and their connections (Weinstein & Mayer, 1983) and prevent rote memorization (Scaife & Rogers, 1996). Throughout a curriculum, learners can add new concepts to their existing concept map. Unlike textbooks, concept maps have no fixed order and may thereby encourage knowledge integration strategies. For example, a student may decide to add the most important or most central concept first. Developing criteria to select concepts requires deeper processing than the student might normally exercise when reading text.

**Table 2.1** Concept mapping for knowledge integration

| Knowledge integration process | KIM activity |
|---|---|
| Eliciting existing ideas | KIMs can be used as a pretest activity to elicit existing concepts |
| Adding new ideas and connecting to existing ideas in repertoire | New concepts can be added to existing propositions in the KIM. If several alternative relations between two concepts are possible, students have to decide which one to use in the map. If applicable, students decide which concepts to add to the map |
| Distinguishing/critiquing ideas | After adding new concepts, concepts can be rearranged into new groups, and the KIM network structure might need revision to reflect the new concepts |
| Sorting out ideas/refining | Different sources of evidence can be used as reference to sort out concepts and further refine the KIM |
| Applying ideas | KIMs can be used as resources to generate explanations of scientific phenomena |

Students need to develop meta-cognitive strategies to distinguish alternative concepts, for example through predicting outcomes and explanation generation (Bransford, Brown, & Crocking, 2000a). The scaffolded process of adding and revising concept maps requires students to decide which concepts and connections to include. The decision-making process may foster the generation of criteria to distinguish pivotal concepts. Clustering-related concepts in spatial proximity can support learners' reflections on shared properties of and relations between concepts. Cross-links between related concepts can be seen as indication for knowledge integration across different contexts. Concept maps may support making sense of concepts by eliciting semantic relationships between concepts (see Table 2.1 above).

Knowledge integration suggests that a successful curriculum starts by eliciting concepts about scientific phenomena. Learners need tools to elicit their concepts and distinguish alternative concepts. Concepts (or ideas) cannot be understood in isolation. Concepts need to be connected to existing concepts, and their meaning can only be understood within such an integrated framework (Bruner, 1960). Learning a concept means seeing it in relation to other concepts, distinguishing it from other concepts, and being able to apply it in specific contexts. To learn a subject is to have actively integrated key concepts and the relations between them.

Knowledge integration activities are designed to help learners construct more coherent understanding by developing criteria for the concepts that they encounter. Research suggests that concept mapping is especially efficient, in comparison to other interventions such as outlining or defining concepts, for the learning of relations among concepts (Canas, 2003). Concept maps as a knowledge integration tool allow eliciting and critiquing concepts and relations between concepts. The visual format of concept maps can foster critical distinctions between alternative concepts and relations, either individually or through collaboration in communities of learners.

Cognitive science (Bransford et al., 2000a) research found that new concepts need to be connected to existing concepts to be stored in long-term memory. Eliciting existing concepts brings them from long-term memory to working memory. Learners make sense of new concepts by integrating them into their existing repertoire of concepts.

Knowledge integration suggests that concepts should be presented in multiple contexts and support generation of connecting concepts across contexts. Multiple representations of concepts (for example dynamic visualizations, animations, pictures, diagrams) can facilitate learning and performance supporting different accounts of scientific phenomena (Ainsworth, 2006; Pallant & Tinker, 2004), for example by complementing each other or constraining interpretations (Ainsworth, 1999). However, having learners make connections between different representations can be challenging as they are connected through multiple relations that are often not intuitively obvious to the learner (Duncan & Reiser, 2005).

## 2 Knowledge Integration Map

Knowledge needs to be structured to be meaningful (Bransford, Brown, & Crocking, 2000b). David Ausubel (Ausubel, 1963; Ausubel, Novak, & Hanesian, 1978) discussed the importance of the hierarchical arrangement of information within organizational tools. Evolution concepts, however, are not necessarily hierarchically organized but consist of concepts from different fields. Research indicates that re-representing text in a concept mapping format can be done in a fairly automated way without requiring construction of new or revision of existing connections between concepts (Holley, Dansereau, & Harold, 1984; Karpicke & Blunt, 2011). Greater benefit may arise if the concept map activity constrains concepts and relations to a novel format, for example by providing biology-specific scaffolding to distinguish "genotype concepts" and "phenotype concepts." The distinction between phenotype and genotype is fundamental to the understanding of heredity and development of organisms (Mayr, 1988). Bruner stated that "virtually all cognitive activity involves and is dependent on the process of categorizing" (Bruner, Goodnow, & Austin, 1986), p. 246). Providing such scaffolding for sorting out and grouping related concepts into categories can support knowledge integration of evolution concepts.

A novel form of concept map, called KIM, aims to elicit and scaffold cross-field connections through the spatial arrangement of concepts in specified levels (see Table 2.2). Markham (Markham, Mintzes, & Jones, 1993) found that the major differences in content knowledge of novices and experts are a lack of integration, lack of cross-links between concepts, and a limited number of hierarchical levels. Integrating complex concepts in fields such as evolution requires connecting concepts from different fields (for example genetics, cell biology, and evolution).

Concept mapping tasks are found in many different forms and provide different amounts of constraints. The task ranges from low directed maps where students can

**Table 2.2** Characteristics of knowledge integration maps (KIMs)

| | |
|---|---|
| Biology-specific levels | This characteristic combines aspects of concept mapping with aspects of Venn diagrams. The KIM drawing area is divided into several domain-specific vertical levels, for example genotype and phenotype. This arrangement requires learners to (a) generate criteria and categorize concepts, (b) sort out concepts into according levels (clustering), and (c) generate connections between concepts within and across levels. Sorting out and grouping concepts spatially according to semantic similarity require learners to generate criteria and make decisions about information structure that is latent in texts (Nesbit & Adesope, 2006). This is expected to support knowledge integration by showing concepts in contexts to other concepts and eliciting existing (and missing) connections within and across levels. Cross-links are especially desirable as they can be interpreted as "creative leaps on the part of the knowledge producer" (Novak & Canas, 2006) and support reasoning across ontologically different levels (Duncan & Reiser, 2007) |
| Given list of concepts, but free labels and links | Many students have difficulties distinguishing important concepts in a text, lecture, or other forms of presentation. Part of the reason is that many students learn only to memorize but not distinguish and sort out concepts. They fail to construct propositional frameworks and see learning as "blur of myriad facts, dates, names, equations, or procedural rules to be memorized, especially in science mathematics and history" (Novak & Canas, 2006). [AU2] Ruiz-Primo et al. (2000) compared concept mapping tasks with varying constraints and found that constructing a map using a given list of concepts (forced choice design) reflected individual student differences in connected understanding better than more constrained fill-the-map forms. Complex topics, such as evolution, consist of a large number of concepts that often make it challenging for novices to identify key concepts. Providing students with a list of expert-selected key concepts can serve as signposts and model expert understanding. Concept maps generated from the same set of concepts allow for better scoring and comparison. Students' alternative concepts are captured in the concept placement, link labels, and link direction. Knowledge integration maps can help students in eliciting relations between concepts, distinguishing central concepts, and making sense of complex science topic such as evolution |
| Concept map training activity | Students need initial training activities to learn the concept mapping method and generate criteria for concept map critique |
| Starter map | Building a KIM from scratch can be challenging. Providing a starter map as a partially worked example could reduce anxiety (Czerniak & Haney, 1998). Critiquing and revising concept maps with starter maps require a completion strategy (Chang, Chiao, Chen, & Hsiao, 2000; Sweller, Van Merrienboer & Paas, 1998) |
| Collaborative concept map activity | KIMs are generated collaboratively in dyads. As each proposition is constrained to only one link, students are required to negotiate which connection to revise or generate. Students are required to generate criteria and negotiate with their partner |
| Focus question | The domain-specific focus question guides the construction of the KIM as learners select concepts and generate links to answer the focus question (Derbentseva, Safayeni, & Canas, 2007) |
| Feedback and revision | Feedback and revision support students' knowledge integration through revisiting, reflecting, and revising existing and new concepts. Concept maps often need several revisions to adequately answer the focus question. Kinchin (Kinchin, De-Leij, & Hay, 2005) suggested that generating several new concept maps could support revisiting concepts better than continuously revising one concept map. Starting new maps allows reviewing superordinate structures that otherwise persist without revision |
| Tools | KIMs can be generated using paper-and-pencil or digital concept mapping tools such as Cmap (Canas, 2004) |

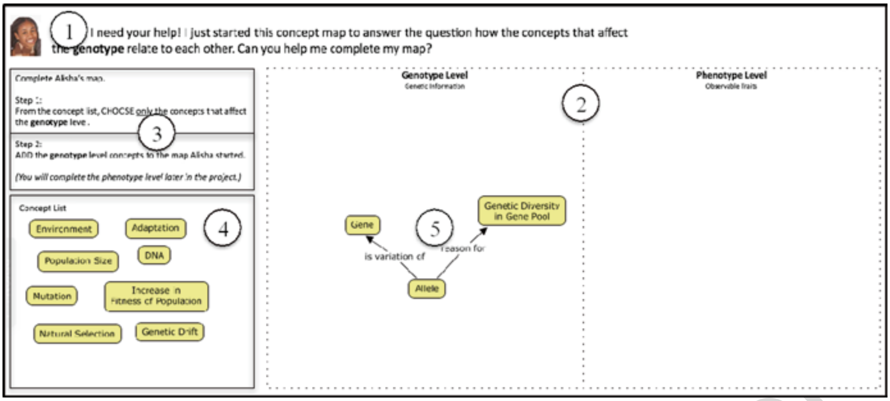



**Fig. 2.1** Knowledge integration map worksheet

freely choose their concepts and labels to highly directed tasks where students fill in concepts out of a given list into blanks in a given skeletal network structure (Novak & Canas, 2006). Highly constrained maps can be beneficial for low-performance and younger students, although they provide less insight into students' partial knowledge. Free drawing concept maps provide the most insight but do not allow for standardized comparisons between students. Constraining students by providing them with a set of concepts or link labels allows for standardized or even automated comparison across students on the exact same content but appears to be more challenging for many students than working from memory. They must discipline themselves to use the given concepts rather than to freely follow their thought patterns (Fisher, Wandersee, & Moody, 2000). KIMs aim for a balanced design by providing students with a small set of concepts but allowing them to generate their own connections and labels. This design allows comparing maps of different students with each other. KIM worksheets consist of five elements: (1) focus question, (2) evolution-specific levels (genotype and phenotype), (3) instructions, (4) given list of concepts, and (5) starter map (see Fig. 2.1).

KIM tasks are created through the process: (1) Generate focus question; (2) based on domain-experts and textbooks, identify key concepts for the map that allow answering the focus question adequately; (3) structure concept map into field-specific levels, for example in biology: genotype/phenotype or individual/population; in chemistry: micro/macro/symbolic; (4) create a starter map; (5) create a concept map training activity. KIMs model what experts consider important concepts by providing a list of expert-selected concepts. Kinchin (2000a) noted that the number of given concepts should be kept small (around 10–20) to reduce complexity and time consumption.

Based on an evaluation of major biology textbooks, state standards, and interviews with experts (for a discussion on expertise, see for example Chi, Glaser, & Rees 1982; Schvaneveldt et al. 1985; Scardamalia & Bereiter, 1991; Hoffman, 1998), 11 concepts have been selected for the forced-choice design of the KIM.

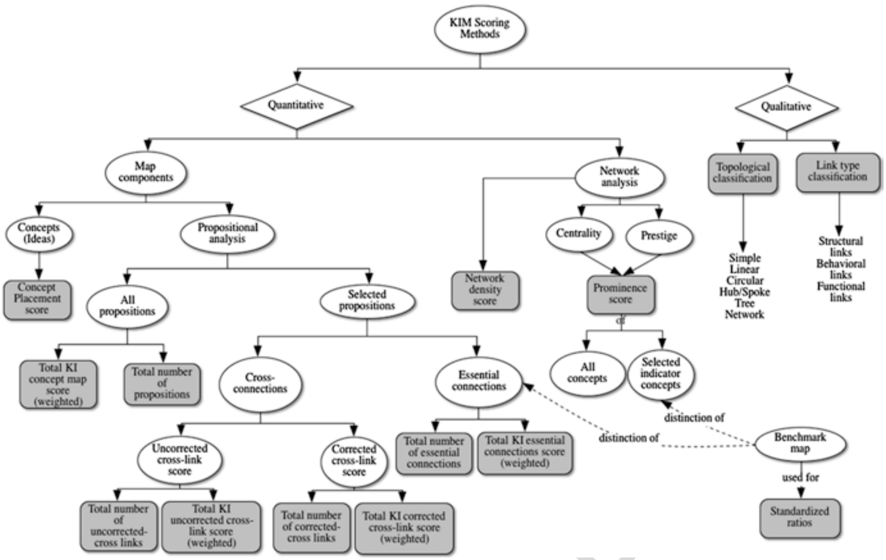



**Fig. 2.2** Overview of KIM analysis methods



The number of concepts was kept low in order to keep to size and complexity of the KIM reasonable for the given time constraints for its creation. A total of 55 connections are possible between the given 11 concepts, but not all propositions are of equal importance. (Considering each direction individually and allowing for circular links to same concept, $11 \times 11 = 121$ connections are possible.) Students need to decide which connections are essential to represent their understanding. Additionally, each connection can go in either direction and be described by many different labels. Students need to match the directionality of the connection with the label and construct a label that accurately describes the nature of relations. As the map constrains students to only one connection for each relation, the students need to develop decision-making criteria. Students are free to generate their own links and labels. To model expert understanding, the given list of concepts includes only expert concepts but no alternative concepts such as "need," "intentionality," or "want." Alternative concepts can be expressed through concept placement and link labels.

## *2.1 Forms of KIM Analysis*

Literature indicates that concept map analysis is no trivial task and can use a wide variety of scoring methods (see the following discussion of quantitative and qualitative analysis methods). Concept maps can be analyzed either qualitatively or quantitatively. Figure 2.2 provides an overview of different KIM analysis methods.

### 2.2 *Quantitative Concept Map Analysis*

The inclusion of concept maps as large-scale assessment tools, for example those used in the 2009 NAEP exam in science (Ruiz-Primo, Iverson & Yin, 2009), requires economical as well as reliable and valid scoring methods. Several studies reported the validity and reliability of quantitatively evaluating concept maps as assessment tools (for example Ifenthaler, 2010; Markham, Mintzes, & Jones, 1994; Ruiz-Primo, 2000; [AU3] Ruiz-Primo et al., 2009; Ruiz-Primo, Schultz, Li, & Shavelson, 2001; Ruiz-Primo, Schultz, & Shavelson, 1997; Ruiz-Primo & Shavelson, 1996; Stoddart, Abrams, Gasper, & Canaday, 2000; Yin, Vanides, Ruiz-Primo, Ayala, & Shavelson, 2005).

Concept maps contain several elements that can be quantitatively evaluated: concepts, hierarchy levels, propositions, and the overall network structure. Links and concepts can be easily counted, but their amount provides little insight into a student's understanding. A higher number of links does not necessarily mean that the student understands the topic better as many links might be invalid or trivial (Austin & Shore, 1995; Herl, 1999). Evaluating the number of hierarchy levels has been suggested by Novak (Novak & Gowin, 1984). The existence of hierarchies is linked to a higher level of expertise, but hierarchy levels can be difficult to differentiate and some concept maps can be non-hierarchical but still valid maps. Propositions, the composite of two concepts, a link label, and an arrow can be evaluated in order to learn about students' understanding. It can be decided to evaluate all propositions equally, to weight certain propositions more than others (Rye & Rubba, 2002), or to analyze only certain indicator propositions (Ruiz-Primo et al., 2009). Yin et al. [AU4] (2005) showed that scoring each individual proposition on a four-point individual proposition scale, summed up to a "total accuracy score," provided the best validity: 0 for scientifically wrong or irrelevant propositions, 1 for partially incorrect propositions, 2 for correct but scientifically "thin" propositions, and 3 for scientifically correct and strong propositions. The "total accuracy score" allows comparing the overall quality of students' concept maps. The disadvantage of this method is its time consumption, and equal evaluation of links that show deeper understanding and trivial links. Yin et al. (2005) compared the total accuracy score to a second concept map scoring method, the convergence score. Propositions of the students' concept map are compared to an expert-generated benchmark map. The convergence score is the proportion of accurate propositions out of all possible propositions in the benchmark map. Concept maps can contain large number of rather trivial connections. An alternative to scoring all links is to focus only on a small number of selected links (Yin et al., 2005). Ruiz-Primo et al. (2009) suggest that scoring only essential links is more sensitive to measuring change because it focuses only on the key concepts of the concept map.

However, analyzing only isolated propositions does not account for the network characteristics of a concept map. Quantitative propositional alone could lead to the same score for a list of isolated propositions and a network of the same propositions. Network analysis can be used to describe the connectedness of a KIM's overall density and prominence of selected indicator concepts.

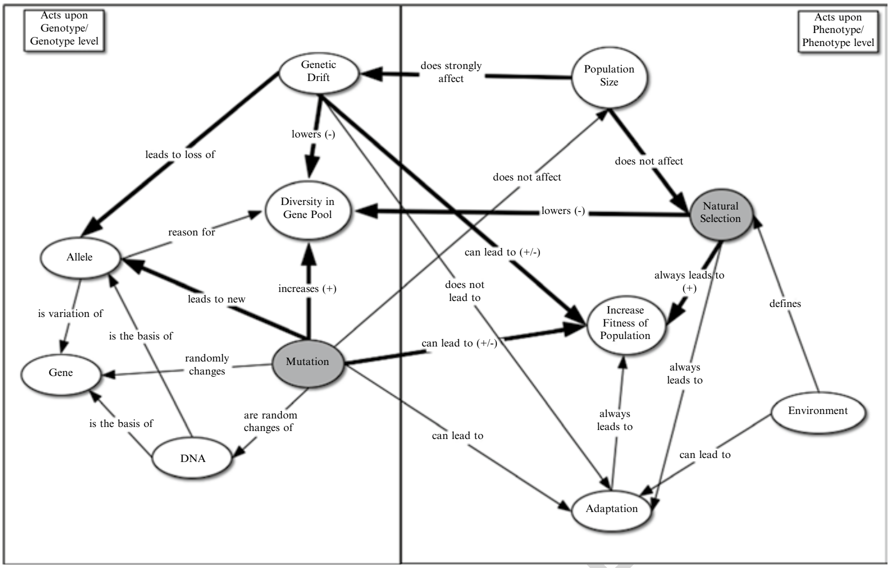



**Fig. 2.3** KIM benchmark map. Indicator concepts (*grey*), essential connections (*bold*)

### 2.2.1 Benchmark KIM

To understand and use concepts, concepts need to be connected to existing concepts. The degree of interconnections between concepts is an essential property of knowledge. One aspect of competence in a field is well-integrated and structured knowledge (Bransford et al., 2000a; Glaser, Chi, & Farr, 1985; Novak & Gowin, 1984). Cognitive psychologists postulate that "the essence of knowledge is structure" (Anderson, 1984, p. 5). An expert-generated KIM can be used to identify the overall structure, central concepts, and essential connections (see Fig. 2.3). However, a benchmark map should not be interpreted and used as the single correct solution but as an expert-generated suggestion that allows identifying central concepts and connections for a detailed analysis. A benchmark KIM can be used to standardize variables to compare different student-generated KIMs against one another. The benchmark KIM indicates how many and which connections experts generate. To calculate standardized KIM variables, student-generated KIM variables are divided by the benchmark KIM variables.

### 2.2.2 Indicator Concepts

Ruiz-Primo suggested that knowledge within a content field is organized around central concepts, and to be knowledgeable in the field implies a highly integrated conceptual structure (Ruiz-Primo et al., 1997). Graphic organizers can enhance

**Table 2.3** Comparison between classical concept maps and KIMs

| Classical concept map | Knowledge integration map |
|---|---|
| No weighted concepts | Weighted concepts (indicator concepts) |
| No weighted relations | Weighted relations (essential connections) |
| Hierarchical arrangement of concepts | Non-hierarchical placement of concepts in domain-specific levels |

student learning by representing complex concepts in an organized structure reflecting the importance of each concept (Plotnick, 1997; Romance & Vitale, 1999). To reverse this finding, learners' understanding of the importance of concepts can be identified by analyzing how connected selected concepts are in a KIM. For the KIM network analysis, one concept from each level (genotype/phenotype) has been selected as the "indicator concept." Indicator concept analysis describes the number and kind of connections to other concepts. The criteria for selecting indicator concepts were (1) centrality in the expert benchmark KIM (see Fig. 2.3) and (2) importance according to evolutionary theory literature:

- For the genotype level, "mutation" has been identified as the indicator concept.
- For the phenotype level, "natural selection" has been identified as the indicator concept.

### 2.2.3 Essential Connections

Ruiz-Primo et al. (2009) found that a KIM analysis that focuses on preselected "essential links" instead of all links can reveal a greater variety of maps while being more time efficient. KIM analysis used ten essential connections (see Fig. 2.3). The criteria for selecting the essential connections were (1) connections between the indicator concepts and the newly introduced concept "gene pool" and "genetic drift" and (2) cross-connections between genotype and phenotype levels. An increased number of cross-connections can be interpreted as a more connected understanding of genotype and phenotype concepts. [AU5]

KIMs differ from classical concept maps in several characteristics (see Table 2.3).

### 2.2.4 KI-Rubric for Concept Maps

To quantitatively describe changes in KIMs from pretest to posttest, primary and secondary analysis variables were used. Primary variables are based directly on the KIMs, while secondary variables are calculated from primary variables. Primary propositional scoring included (1) scoring of all propositions and (2) scoring of only essential propositions.

**Table 2.4** KIM knowledge integration rubric

| KI score | Link label quality | Link arrow | Sample propositions |
|---|---|---|---|
| 0 | None (no connection) | None (no connection) | None |
| 1 | Wrong label | Wrong arrow direction | Genetic variability includes mutation |
| 2 | No label | Only line | Mutation -- genetic variability |
| | Correct label | Wrong arrow direction | Genetic variability –contributes to > mutation |
| | Incorrect label | Correct arrow direction | Mutation – includes > genetic variability |
| 3 | No label | Correct arrow direction | Mutation --> Genetic Variability |
| 4 | Partially correct label | Correct arrow direction | Mutation – increases -> Genetic Variability |
| 5 | Fully correct label | Correct arrow direction | Mutation – causes random changes in the genetic material which in turn increases -> Genetic Variability |

1. Score all propositions
   KIM propositions consist of two concepts and their relation (indicated by a labeled line with an arrowhead). Propositions are the elementary units of KIMs. Individual propositions were analyzed using a five-level knowledge integration rubric (see Table 2.4). All propositions were weighted equally.
2. Score only essential propositions
   Using the same five-level knowledge integration rubric (see Table 2.4), only essential propositions were scored (see Fig. 2.3).

### 2.2.5 Concept Placement Analysis

KIMs ask students to sort out concepts into domain-specific levels (for example genotype and phenotype). Concept placement is an additional level of information that indicates how students categorize concepts. Connecting concepts within a level indicates students' understanding of the relations between closely related concepts. Connecting concepts across levels (cross-links) indicates students' understanding across ontologies and levels of space and time. Cross-links are of particular interest as they can indicate "creative leaps on the part of the knowledge producer" (Novak & Canas, 2006) and reasoning across ontologically different levels (Duncan & Reiser, 2007). Cross-links are relations between concepts in different levels. Cross-connections are of particular interest as they indicate if students see connections between genotype- and phenotype-level concepts. As concepts might be wrongly placed by students, an observed cross-connection might actually be a connection

**Table 2.5** KIM primary variables: Number of links

| Variable name | Description |
|---|---|
| Total number of links | Number of links in the KIM |
| Total number of essential links | Number of essential links in the KIM |
| Total number of uncorrected cross-links | *Uncorrected* cross-links are connections that cross the line between the genotype and phenotype level. Because of falsely placed concepts, the connection might not be a true cross-connection between a genotype- and phenotype-level concept. However, the uncorrected cross-link can be seen as an indicator for students' motivation to connect concepts across levels |
| Total number of corrected cross-links | *Corrected* cross-links count connections between genotype- and phenotype-level concepts, even if the concepts were wrongly placed |

between two concepts of the same level ("uncorrected cross-link"). To account for such cases, a "corrected cross-link" variable indicates intra-domain connections even if the concepts were wrongly placed.

### 2.2.6 Primary Analysis Variables

Two different sets of primary variables were created: non-weighted number of links (see Table 2.4) and links weighted by their respective knowledge integration (KI) scores (see Table 2.5).

1. Primary variables: Number of links (see Table 2.5).
   As propositions may differ not only in quantity but also quality, propositions were weighted by multiplying them with their respective KI scores (see Table 2.4).
2. Primary variables: Knowledge integration scores (see Table 2.6).

### 2.2.7 KIM Secondary Analysis Variables

Another way to describe quantitative changes in KIMs is density variables and ratios (calculated from primary analysis variables). Ratios and densities can be relative or standardized (see Table 2.7).

## *2.3 KIM Network Analysis*

Research suggests that concept maps can assess different forms of knowledge than conventional assessment forms (Ruiz-Primo, 2000; Shavelson, Ruiz-Primo, &

**Table 2.6** KIM primary variables

| Variable name | Description |
|---|---|
| Total KI score of all links (total accuracy score) | Product of total number of links and their respective KI scores |
| KI score essential links | Product of total number of essential links and their respective KI scores |
| KI score genotype level only | Product of number of links in the genotype-level area (not counting cross-links) and their respective KI scores |
| KI score phenotype level only | Product of number of links in the phenotype-level area (not counting cross-links) and their respective KI scores |
| KI score uncorrected cross-connections | Product of number of uncorrected cross-connections and their respective KI scores |
| KI score corrected cross-connections | Product of number of corrected cross-connections and their respective KI scores |

**Table 2.7** KIM secondary variables

| Variable name | Description |
|---|---|
| Relative density | Total number of student-generated connections divided by total number of possible connections (=55) |
| Standardized density | Total number of student-generated connections divided by total number of links in benchmark map (=23) |
| Relative essential link ratio | Total number of essential student-generated connections divided by total number of student-generated connections |
| Standardized essential link ratio | Total number of essential student-created connections divided by total number of essential connections in benchmark map (=10) |
| Corrected cross-connections ratio | Total number of student-generated cross-connections (corrected) divided by total number of cross-connections in benchmark map |
| KI score ratio | Total KI score in student-generated map divided by total KI score in expert-generated benchmark map (=126) |
| Standardized KI score ratio | Total KI score of essential connections in student-generated map divided by total KI score of essential connections in benchmark map (=50) |



Wiley, 2005; Yin et al., 2005), for example knowledge structure and cross-connections. However, the commonly used quantitative propositional method of analysis does not capture changes in the overall network structure. Network analysis uses the frequency of usage of essential concepts as indicators for a more integrated understanding. The network analysis method is based on social network analysis (Wasserman & Faust, 1994). As students develop a more complex understanding, they might also identify certain concepts as more important and connect them more often. In the KIM example used in this chapter, the indicator concepts "mutation" (genotype level) and "natural selection" have been selected (see Fig. 2.3). Two measurements were used to capture changes in connection frequencies to the indicator concepts.

Network analysis method can identify changes in "centrality" (outgoing connections) and "prestige" (incoming connections) of expert-selected indicator concepts (mutation for genotype level; and natural selection for phenotype level).

- *Centrality*: Outgoing connections from the indicator concept. This variable describes how many relations lead away from the indicator concept.
- *Prestige*: Incoming connections to the indicator concept. This variable describes how many relations from other concepts lead to the indicator concept.

The two network variables centrality and prestige can be combined to a total "prominence score" (importance indicator) for each indicator concept. Multiplied with the KI score for each connection, a "weighted prominence score" for each of the two indicator concepts can be calculated.

An adjacency matrix was used to establish centrality and prestige of each indicator concept. The adjacency matrix, sometimes also called a connection matrix, is a matrix with rows and columns labeled by graph vertices, with a 1 or a 0 in position according to whether two concepts are adjacent or not (Chartrand & Zhang, 2004; Pemmaraju & Skiena, 2003). The expert-generated KIM benchmark was used to determine benchmark values of centrality and prestige.



## *2.4 Qualitative KIM Analysis*

Qualitative analysis methods complement quantitative descriptions of concept maps by tracking changes in the geometrical structure (topology) and types of propositions.

### 2.4.1 KIM Topological Analysis

Quantitative analysis methods focus only on isolated propositions and therefore cannot give an account of the network character of a whole map. Kinchin (2000b, 2001) suggested a framework of four classes (simple, chain/linear, spoke/hub, net) to describe the major geometrical structure of a concept map. A "network" structure indicates a more integrated understanding than a "fragmented" concept map structure. However, a ranking of these categories is only possible at the extreme ends, with "fragmented" at one end and "networks" at the other. All other classes fall in between. Yin et al. (2005) extended Kinchin's framework by two additional classes (tree and circle) (see Table 2.8):

(0) Simple: Mostly isolated propositions.
(1) Chain: Propositions are in a linear chain.
(2) Tree: Linear chain but with branches.
(3) Hub: Connections emanate from a center concept.
(4) Circular propositions: Propositions are daisy-chained forming a circle.
(5) Network: Complex set of interconnected propositions.

**Table 2.8** Concept map topological categories (adapted from Yin et al., 2005)

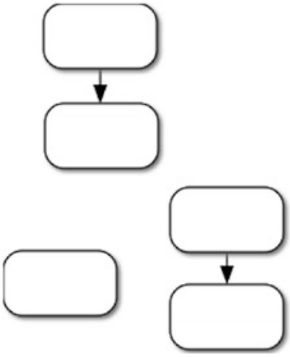
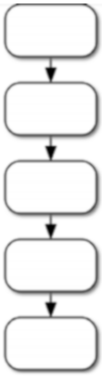
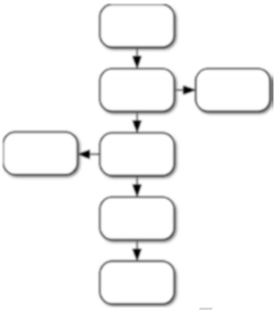
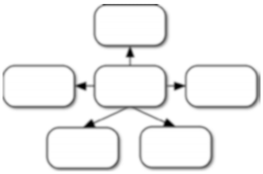
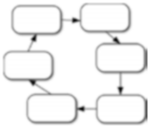
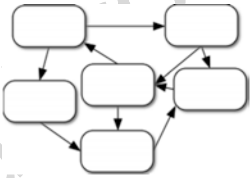
| | | |
|---|---|---|
|  |  |  |
| Simple/fragmented | Chain/linear | Tree |
|  |  |  |
| Hub/spoke | Circular | Network |

**Table 2.9** Topological KIM categories (for a two-area KIM)

| First area | Second area |
|---|---|
| Empty | Empty |
| Fragmented | Fragmented |
| Linear | Linear |
| Tree | Tree |
| Hub | Hub |
| Circular | Circular |
| Network | Network |



The analysis methods developed for KIMs further extend Yin's framework. As KIMs are divided into domain-specific levels (for example genotype and phenotype), the geometrical structure of each level needs to be described (see Table 2.9). Coding includes each possible combination of geometrical structures in the two levels. Changes in the topology of KIMs can indicate changes in students' knowledge integration.

### 2.4.2 Qualitative Proposition-Type Analysis

Learning about relations between concepts is challenging for all learners. When learning a language, students learn nouns before verbs (Gentner, 1978). Typically, KIM concepts are nouns while link labels are verbs. Learning about the relations

**Table 2.10** Categories of different types of KIM relations

| Super-category | Sub-category | Code | Examples |
|---|---|---|---|
| UNRELATED | No connection | 0 | |
| | No label (just line) | 1 | |
| | Unrelated label | 2 | |
| STRUCTURE What is the structure (in relation to other parts)? | Part–whole (hierarchical) | 3 | Is a/are a; is a member of; consist of; contains; is part of; made of; composed of; includes; is example of |
| | Similarity/comparison/contrast | 4 | Contrasts to; is like; is different than |
| | Spatial proximity | 5 | Is adjacent to; is next to; takes place in |
| | Attribute/property/characteristic (quality (permanent) or state (temporary) | 6 | Can be in state; is form of |
| BEHAVIOR What action does it do? How does it work/ influence others? | Causal-deterministic (A always influences B) | 7 | Contributes to; produces; creates; causes; influences; leads to; effects; depends on; adapts to; changes; makes; results in; forces; codes for; determines |
| | Causal-probability (modality) | 8 | Leads to with high/low probability; often/rarely leads to; might/could lead to; sometimes leads to |
| | Causal-quantified | 9 | Increases/decreases |
| | Mechanistic | 10 | Explains domain-specific mechanism/ adds specific details or intermediary steps |
| | Procedural-temporal (A happens before B) | 11 | Next/follows; goes to; undergoes; develops into; based on; transfers to; happens before/during/after; occurs when; forms from |
| FUNCTION Why is it needed? | Functional | 12 | Is needed; is required; in order to; is made for |
| | Teleological | 13 | Intends to; wants to |



between concepts can be more challenging than understanding concepts. However, understanding the relations between concepts is essential to an integrated understanding of biology.

Most existing concept map analyses focus on quantitative variables (see Sect. 2.2). To describe semantic changes in the relations between concepts, qualitative variables are needed. To track changes in relation types, a link label taxonomy has been developed for KIMs (see Table 2.10). The relation categories also include negations, e.g., "does not lead to" or "is not part of."

The concept mapping literature suggests a number of different link types. For example, Fisher (2000) distinguished three main types of propositional relations in biology that are used in 50 % of all instances: *whole/part*, *set/member*, and *characteristic* (p. 204). O'Donnell distinguished between three types of relations in knowledge maps: dynamic, static, and elaboration (O'Donnell, Dansereau, & Hall, 2002). Lambiotte suggested dynamic, static, and instructional relation types for concept maps (Lambiotte, Dansereau, Cross, & Reynolds, 1989). Derbentseva distinguished between static and dynamic relations in concept maps (Derbentseva et al., 2007; Safayeni, Derbentseva, & Canas, 2005).

To create a taxonomy of link types, higher order variables are needed. KIM analysis used the structure–behavior–function (SBF) framework to create the super-categories of the taxonomy. The SBF framework was originally developed by Goel (Goel & Chandrasekaran, 1989; Goel, Rugaber, & Vattam, 2008) to describe complex systems in computer science and then applied to complex biological systems by Hmelo-Silver (Hmelo-Silver, 2004; Hmelo-Silver, Marathe, & Liu, 2007; Liu & Hmelo-Silver, 2009).

- Structure: What is the structure (in relation to other parts)? These variables describe static relations between concepts. Static relations between concepts indicate hierarchies, belongingness, composition, and categorization.
- Behavior: What action does it do? How does it work/influences others? These variables describe the dynamic relations between concepts. Dynamic relations between concepts indicate how one concept changes the quantity, quality, or state of the other concept.
- Function: Why is it needed? These variables describe functional relations between concepts, for example “want” (intentionality) or “need” (teleological).

The sub-categories for the taxonomy emerged from KIM analysis (see Table 2.10). Categorizing link labels allows tracking and describing how connections changed ontologically.

## 3 Discussion and Implications

This chapter introduced KIMs as a novel form of concept map and illustrated how a combination of qualitative and quantitative analysis methods can provide complementary information to triangulate changes in learners’ understanding of complex topics, such as evolution. KIMs can be rich sources for students’ alternative ideas. KIMs can contain different forms of information: presence or absence of connections, quality of connections, different types of link labels, different types of networks, and spatial placement of concepts. To account for these different aspects of KIMs, different analysis strategies need to be applied to triangulate changes in understanding of learners. KIMs provide an additional layer of information by structuring the drawing area into domain-specific areas. As a learning tool, the KIM areas aim to support learners’ meaningful structuring of concepts by modeling expert understanding. KIMs can be used in different stages of curriculum development and implementation: As curriculum planning tools, KIMs can be used to identify core concepts and essential connections. As learning tools, KIMs can be used for individual or collaborative generation activities. As assessment tools, KIMs can be used to identify alternative concepts, elicit existing and missing connections within and across levels, categorization of concepts, overall network structure, and prominence of important concepts. This chapter used an example from biology to illustrate KIM [AU6] generation and analysis; however, KIMs can be implemented in a wide variety of different fields.

Concept maps as assessment tools have been used to track conceptual change in a wide variety of contexts (Edmondson, 2000; Mintzes, Wanderersee & Novak, 2001; Ruiz-Primo, 2000b; Ruiz-Primo & Shavelson, 1996). Since 2009, concept [AU7] maps have been used in addition to traditional assessment tools in standardized large-scale assessments in the US National Assessment of Educational Progress (NAEP) (Ruiz-Primo et al., 2009) to measure changes in conceptual understanding of science concepts. Concept maps can reveal students' knowledge organization by showing connections, clusters of concepts, hierarchical levels, and cross-links between concepts from different levels (Shavelson et al., 2005). Concept map analysis, especially of more constrained forms, has been found to be reliable and valid (Markham et al., 1994; Michael, 1995; Ruiz-Primo et al., 1997, 2001; Rye & Rubba, 2002; Shavelson et al., 2005; Stoddart et al., 2000; Yin et al., 2005). Less constrained forms of concept maps can include many different kinds of concepts and connections. The amorphousness and arbitrariness of structure, mixture of different kinds of concepts (for example physical object, process, abstract construct, property), and different types of links (for example causal, correlational, temporal, part–whole, functional, teleological, mechanical, probabilistic, spatial) can make analysis challenging and time consuming (McClure et al., 1999). This chapter identified several methods and variables, such as KIM cross-links, indicator concepts' prominence scores, weighted essential link scores, network analysis, topological analysis, and qualitative propositional analysis, that can be more efficient and sensitive than scoring each proposition in isolation.

Cross-links can indicate the integration of knowledge across levels or domains. Experts and successful students develop well-differentiated and highly integrated frameworks of related concepts (Chi, Feltovich, & Glaser, 1981; Mintzes, Wandersee, & Novak, 1997; Pearsall, Skipper, & Mintzes, 1997). Cross-links are of special interest as they can indicate creative leaps on the part of the knowledge producer (Novak & Canas, 2006).

Network analysis of indicator concepts describes changes of the centrality and prestige of indicator concepts. Improved understanding of a complex topic can be tracked through an increase in the prominence of indicator concepts. Distinguishing certain concepts as being important can be interpreted as a shift from a surface-level understanding to a higher order understanding.

Concept maps aim to represent only selected important connections as not all possible propositions are equally meaningful. More connections do not necessarily mean a better map and deeper understanding. It is not necessary to generate every possible connection and include every possible concept but be purposefully selective. Similarly, concept map analysis can focus on essential links. Essential links can be identified through expert-generated KIMs. Research (Ruiz-Primo et al., 2009; Schwendimann, 2011a, 2011b) suggests that focusing on weighted essential links can reveal a greater variety of understanding while being more time efficient.

The analysis of isolated propositions does not account for the network character of KIMs. Network density and prominence scores of selected indicator concepts can describe changes in the network structure of KIMs.

The topological structure of a KIM can indicate shifts in learners' knowledge structure. A "network" structure indicates a more integrated understanding than a "fragmented" concept map structure.

Qualitative proposition-type analysis can indicate shifts in learners' understanding. For example in evolution education, a shift in the prominence of normative evolution concepts "mutation" and "natural selection" and a decrease of teleological concepts "need" or "want" can indicate an improved understanding of the mechanism of evolution. More quantified relations can be seen as an indicator for deeper understanding (Derbentseva et al., 2007).

## *3.1 KIM Analysis and Benchmark Maps*

Expert-generated KIM benchmark maps can be used to identify central concepts, indicator concepts, and essential connections and establish comparison variables. However, they should not be seen as the only correct solution for direct comparison as there is no single ideal expert benchmark map. Using expert-generated benchmark maps might suggest that there is only one correct answer (Kinchin, 2000a). From a constructivist perspective, concept maps should reflect the rich variety of students' repertoire of concepts. Using only a single expert-generated as the benchmark for direct comparisons does not allow capturing the many ways ideas can be expressed in concept maps. There is no single "expert map" as experts can generate a wide variety of concept maps (Schwendimann, 2007). Expert maps can strongly differ from one another (Acton, Johnson, & Goldsmith, 1994), even when using a limited number of given concepts, and show great variety. Expert-generated concept maps distinguish themselves not necessarily in quantity but in informed selection of important concepts, higher level clustering of concepts, and meaningful connections. Students might try to find the one "correct answer" for a KIM. Instructors should stress the point that each KIM is unique and that there are many different possible solutions for a good KIM, as even experts in the same field generate KIMs that are different from one another.

This also raises the question of who is considered an expert. There are many different kinds of experts, for example researchers, practitioners, proficient amateurs, and science teachers (Hmelo-Silver et al., 2007). An expert benchmark map can be generated by a single expert (Coleman, 1998), the teacher, or a group of experts [AU8] (Osmundson, Chung, Herl, & Klein, 1999). Ruiz-Primo et al. (2001) suggest creating an aggregated expert-group map. Interpreting concept map propositions can be difficult as expert and novices might use the same expressions but with different meaning. Ariew (2003) points out that experts can use seemingly nonnormative expressions as "shorthand" for normative concepts, for example a teleological expressions in biology such as "Beavers developed large teeth because they needed to cut trees." More education research is needed to address the "expert problem" by providing better descriptions of what constitutes an expert and distinguishing different types of experts.

This chapter suggests that scoring propositions using a knowledge integration rubric can reveal a greater variety of students' alternative concepts than a direct comparison to an expert-generated benchmark map (for examples of direct comparisons see Chang, Sung, & Chen, 2001; Cline, Brewster, & Fell, 2009; Herl, O'Neil, Chung, Dennis, & Lee, 1997; Rye & Rubba, 2002). The knowledge integration concept map rubric acknowledges different ways concepts can be expressed. It seems easier to construct concept maps than to make sense of them. Analyzing concept maps can be time consuming and cognitively demanding. Efficient analysis methods are needed if concept maps are to become more widely used as summative or as formative real-time assessment tools (Pirnay-Dummer & Ifenthaler, 2010). The analysis methods described in this chapter were developed for human coders. Automated concept map analysis methods aim to complement or replace coding by hand. Simple automated analysis approaches directly match concept maps to a single expert-generated benchmark map. Direct matching approaches are not sensitive to the rich diversity of alternative ways in which ideas can be expressed in concept maps. Recent approaches for automated analysis aim to alleviate this limitation by using the graphical properties of concept maps or by focusing on the frequencies of selected elements in the map. For example, Hoppe, Engler, and Weinbrenner (2012) developed an algorithm to automatically analyze graphical properties of concept maps without the need for an expert-generated concept map for comparison. Evaluating the frequency of certain propositions (Cathcart et al., 2010) or short chains of propositions (Grundspenkis & Strautmane, 2009) allows describing greater variety of alternative ideas than a direct comparison to an expert map.

No single analysis method can capture and track the rich information present in concept maps. This chapter concludes that only using complementary methods in concert allows describing alternative ideas and triangulating changes in concept maps. A comprehensive analysis of concept maps might combine human and automated evaluation using both quantitative and qualitative methods. Further research is needed to more fully and more efficiently make sense of concept maps.

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# Author Queries

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| Queries | Details Required | Author's Response |
|---|---|---|
| AU1 | Please check if the section headings are assigned to appropriate levels. | |
| AU2 | The cross reference "Ruiz-Primo et al. (2000)" is cited in text but not given in the reference list. Please provide details in the list or delete the citation from the text. | |
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